What is ACCORDS?

Adult and Child Center for Outcomes Research and Delivery Science

ACCORDS is a ‘one-stop shop’ for pragmatic research:

- A multi-disciplinary, collaborative research environment to catalyze innovative and impactful research
- Strong methodological cores and programs, led by national experts
- Consultations & team-building for grant proposals
- Mentorship, training & support for junior faculty
- Extensive educational offerings, both locally and nationally

ACCORDS Upcoming Events

March 6, 2024 AHSB Room 2002, Zoom	**Ethics, Challenges, & Messy Decisions in Shared Decision Making** Critical Conversations: Health Equity Considerations for Working With and In Diverse Communities *Presented by:* Channing Tate, PhD, MPH; Demetria Bolden, PhD, MBA; Lucinda Kohn, MD, MHS, Miria Kano, PhD
March 11, 2024 AHSB 2200/2201, Zoom	**Statistical Methods for Pragmatic Research** Pragmatic Statistical Learning: From Data to Interpretable Insights *Presented by:* Ryan Peterson, PhD & Kathryn Colborn, PhD
April 3, 2024 AHSB Room 2002, Zoom	**Ethics, Challenges, & Messy Decisions in Shared Decision Making** Am Example of Implementing Shared Decision Making with the SHARE Project *Presented by:* Laura Scherer, PhD; Chris Knoepke, PhD, MSW, LCSW
April 15, 2024 AHSB 2200/2201, Zoom	**Statistical Methods for Pragmatic Research** *Presented by:* Michael Matheny, PhD
April 26, 2024 AHSB 2200/2201, Zoom 11am-1pm MT	**ACCORDS/CCTSI Community Engagement Showcase**
May 20, 2024 AHSB 2200/2201, Zoom	**Statistical Methods for Pragmatic Research** Planning a Pragmatic Effectiveness Trial with a Factorial Design by Targeting the Posterior Distribution Variance *Presented by:* Keith Goldfeld, DrPH, MS, MPA/MURP

*all times 12-1pm MT unless otherwise noted

COPRH Con
Colorado Pragmatic Research in Health Conference

Innovations in Pragmatic Research Methods

From Data to Equity, Policy, and Sustainability

June 5 - 6, 2024 | 10am-3:30pm MT

ACCORDS
ADULT AND CHILD CENTER FOR OUTCOMES RESEARCH AND DELIVERY SCIENCE
UNIVERSITY OF COLORADO
CHILDREN'S HOSPITAL COLORADO

Registration is open now at www.COPRHCon.com

bitly

Join ACCORDS D&I Science Program!

Rashelle Musci, PhD

Latent Class Analysis: *Assumptions and Extensions*

Latent Class Analysis: Assumptions and Extensions

Rashelle J. Musci, PhD

Departments of Mental Health, Biostatistics, and Population, Family and Reproductive Health

Johns Hopkins Bloomberg School of Public Health

Training:

University of California, Davis: BS (Neurobiology, Physiology, and Behavior)
University of California, Davis: MS (Child Development)
University of California, Davis: PhD (Human Development
Johns Hopkins SPH & School of Medicine, Post-Doctoral Fellowship

Baltimore Generations Project

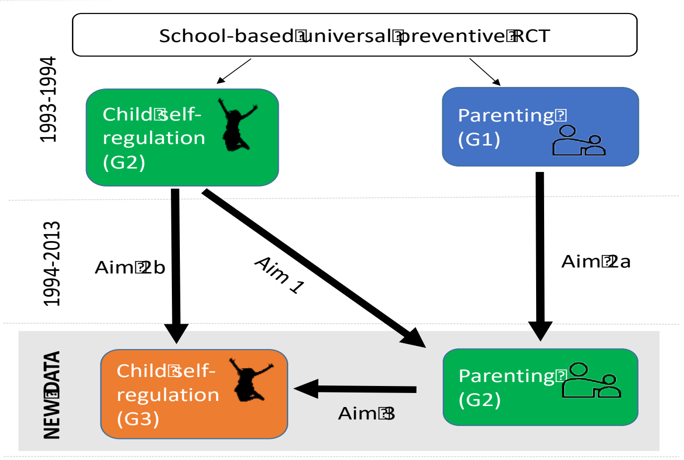


Figure 1: Study overview

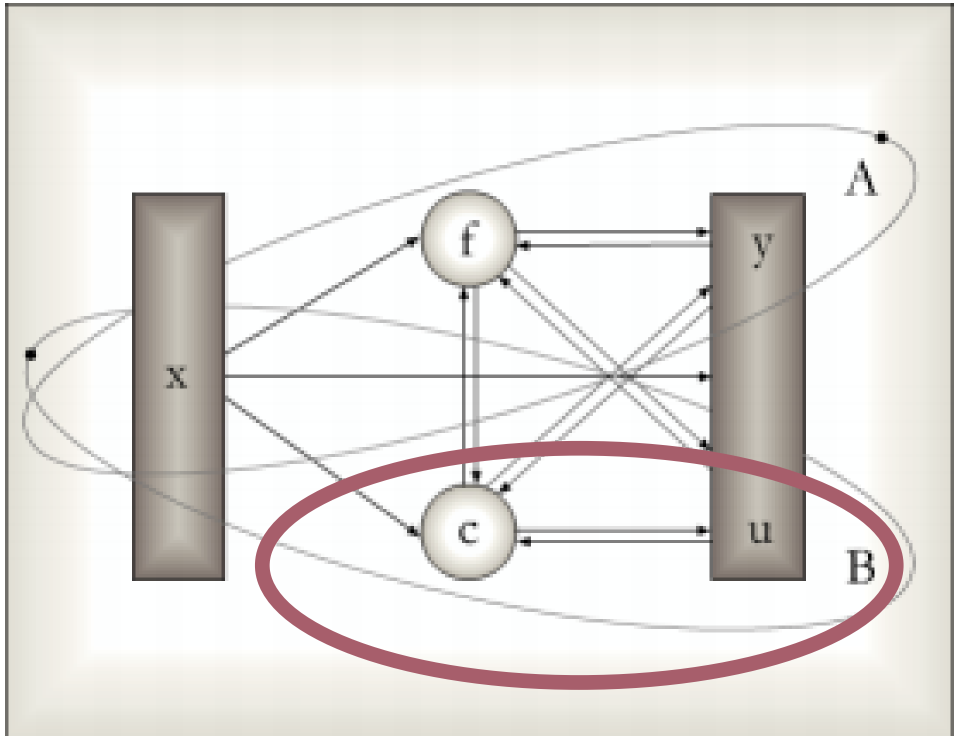
Within the harmonized dataset, we will identify the impacts of prevention programs in early childhood on long-term outcomes including 1) suicidal ideation, attempt and death, and 2) depressive, anxious, and psychotic symptoms and disorders.

Harmonizing data from existing cohorts to investigate environmental exposures -- physical, chemical, biological, social, behavioral, natural and built environments – on child health and development

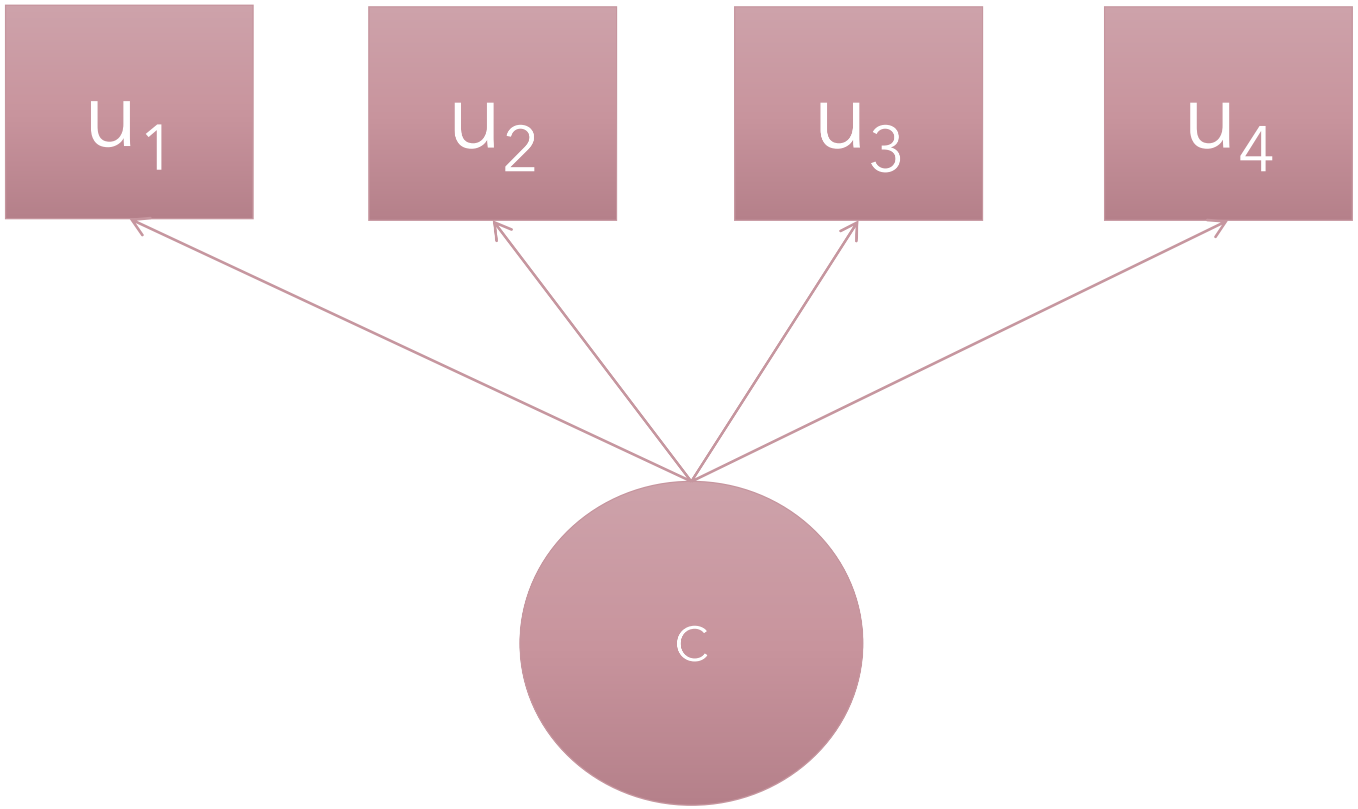
What is latent class analysis?

- A subset of finite mixture models formulated as a mixture of generalized linear models
- Focuses on finding similarities and differences among people
- For a given variable, the observed distribution of values may be a “mixture” of two or more subpopulations whose membership is unknown
- Every individual has a set of probabilities for membership in classes

Modeling framework



- F: continuous latent variable
- C: categorical latent variable
- Y: continuous observed variable
- U: discrete observed variable
- T: continuous event time
- X: observed continuous/ categorical covariate


u_1
u_2
u_3
u_4
c

A sprinkle of formulas

- The conditional probability for each u given c is parameterized in terms of a logistic regression
- In the case of a binary u_j, coded 0/1, the conditional probability simplifies to:
  - $Pr(u_j = 1|c=k) = 1- (1/1+exp(-\tau_{j,k}))$

    $= 1/1+exp(\tau_{j,k})$
  - Such that $\tau_{j,k}$=-logit(u_j)

Estimating a LCA model

- Statistical model fit
  - Log-likelihood
  - $\text{BIC} = -2LL + d \log(n)$,
  - Lo-Mendell-Rubin test (tech11)
  - BLRT (tech14)
  - Standardized residuals
- Model usefulness
  - Substantive interpretation
  - Classification quality
    - Classification tables
    - Entropy

How does it work?

- Estimation done using the EM (expectation-maximization) algorithm
  - Starts with a random split of people into classes
  - Reclassify based on an improvement criterion
  - Reclassify until the best classification of people is found
  - Best classification represents the best likelihood value

More practical issues

- Sample size

  There is no set minimum sample size

  Bare minimum would be around n=20 (??!!)
- Sample size and outcomes influence type and number of classes
- Within-class model used determines the type and number of classes

  Classes are being driven by what you allow to vary within classes

Let's work through an example!

Development and Psychopathology (2023), **35**, 1358–1370
doi:10.1017/S0954579421001255

CAMBRIDGE UNIVERSITY PRESS

Regular Article

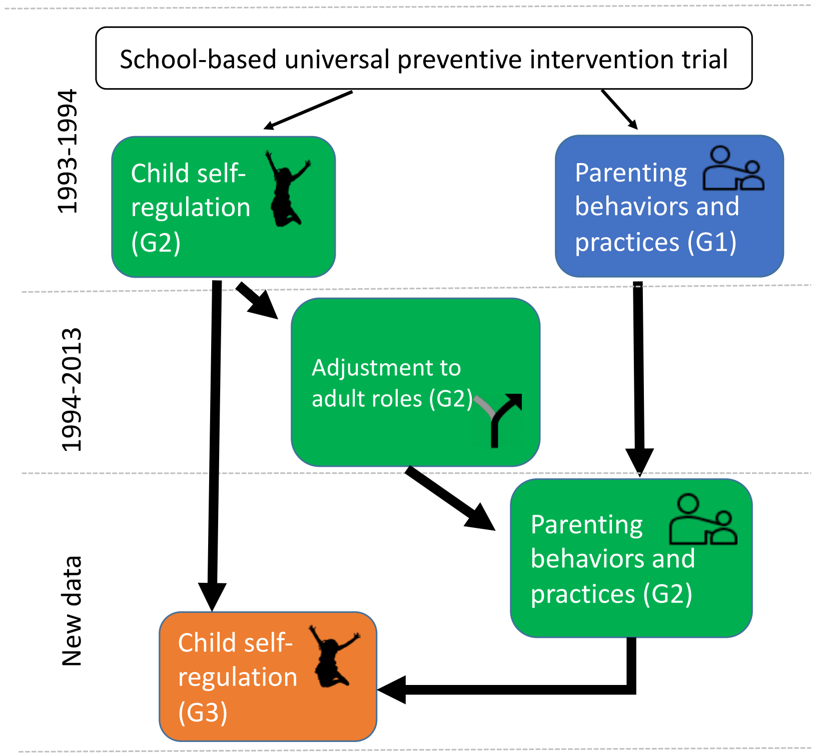
Self-control in first grade predicts success in the transition to adulthood

Sara B. Johnson[1,2,3], Kristin M. Voegtline[1,2], Nicholas Ialongo[3], Karl G. Hill[4] and Rashelle J. Musci[3]

[1]Department of Pediatrics, Johns Hopkins School of Medicine, Baltimore, MD, USA, [2]Department of Population, Family and Reproductive Health, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, USA, [3]Department of Mental Health, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, USA and [4]University of Colorado, Institute of Behavioral Science, Boulder, CO, USA

The Baltimore Generations Study

- This study leverages an existing two-generation cohort of predominately low/middle income African American families in Baltimore (i.e., G1, G2)
- The primary aim is to explore the impact of early self-regulation on outcomes during the transition to adulthood



Methods

- Participants
  - 678 1st graders (M=6.2y, +/-0.34y)
  - Baltimore City Public Schools
  - 53.4% male, 86.3 % Black, 68.3% free or reduced lunch
  - Retention to adult follow-up ~80%
- Assessment
  - Measures of a variety of constructs were collected from participants, parents, and teachers
  - For more information on the intervention see Ialongo et al. (1999)

Measures

Child Self-Regulation, Teacher Report:

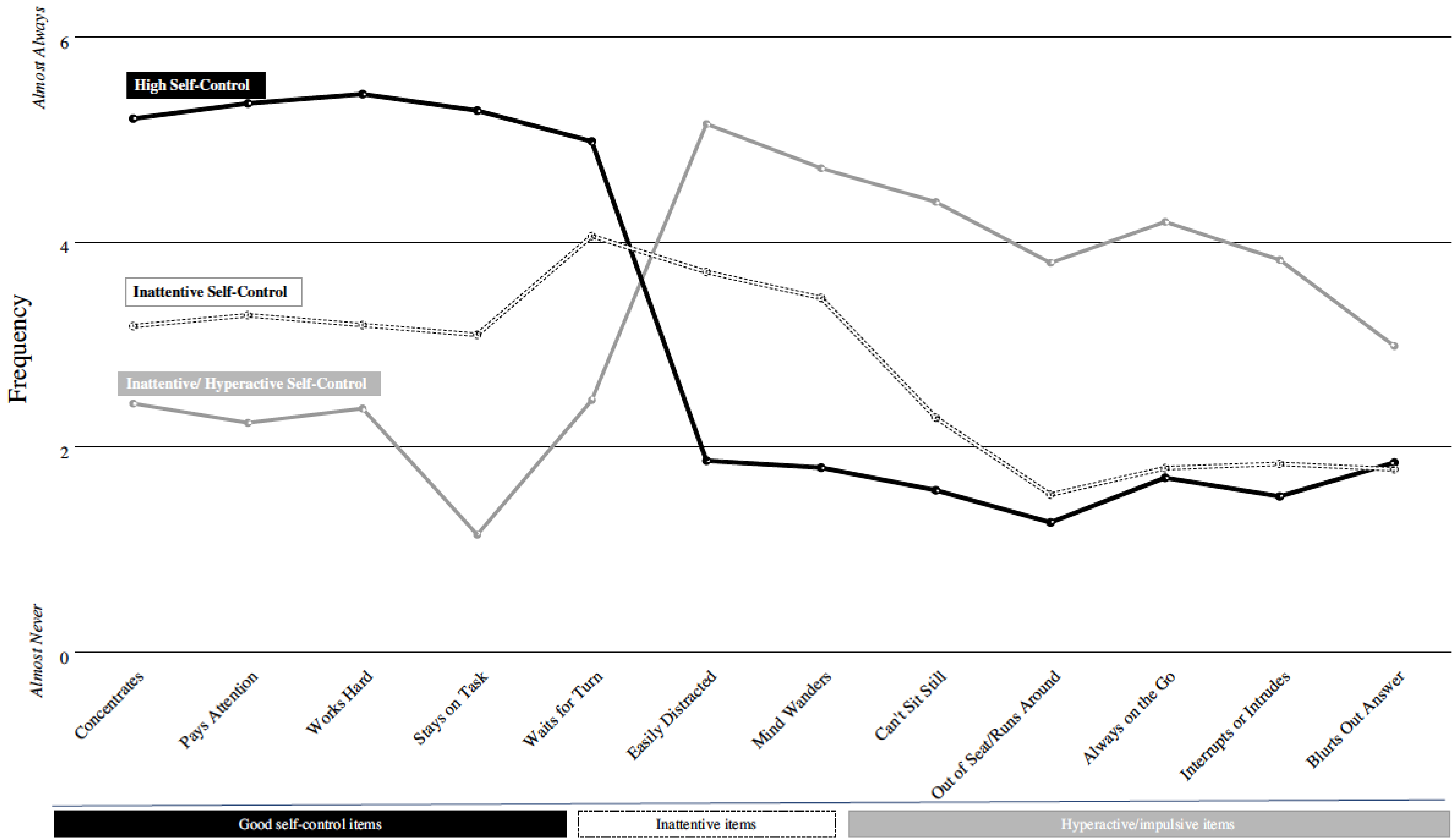
- Teacher Observation of Classroom Adaptation-Revised (TOCA-R)
- Brief measure of child's adequacy of performance on core classroom tasks
- 6 pt. Likert: Almost Never=1 to Always=6

Young adult outcomes, self-report:

- On-time high school graduation
- College participation
- Teenage pregnancy
- Substance use disorder
- Incarceration
- Criminal justice system involvement

Fitting our latent class variable

No. of classes	# of free par.	Log Likelihood	BIC	LRT	Entropy	Smallest Class
2	40	-12840.2	25941.1	3486.3, <0.001	0.95	306 (45.5%)
3	56	-12184.4	24733.3	1312.0, 0.002	0.94	112 (16.7%)
4	72	-11921.8	24312.4	525.0, 0.53	0.91	99 (14.7%)
5	88	-11689.1	23951.1	465.5, 0.54	0.92	73 (10.9%)



Almost Always
Almost Never
Frequency
6
4
2
0
High Self-Control
Inattentive Self-Control
Inattentive/ Hyperactive Self-Control
Concentrates
Pays Attention
Works Hard
Stays on Task
Waits for Turn
Easily Distracted
Mind Wanders
Can't Sit Still
Out of Seat/Runs Around
Always on the Go
Interrupts or Intrudes
Blurts Out Answer
Good self-control items
Inattentive items
Hyperactive/impulsive items

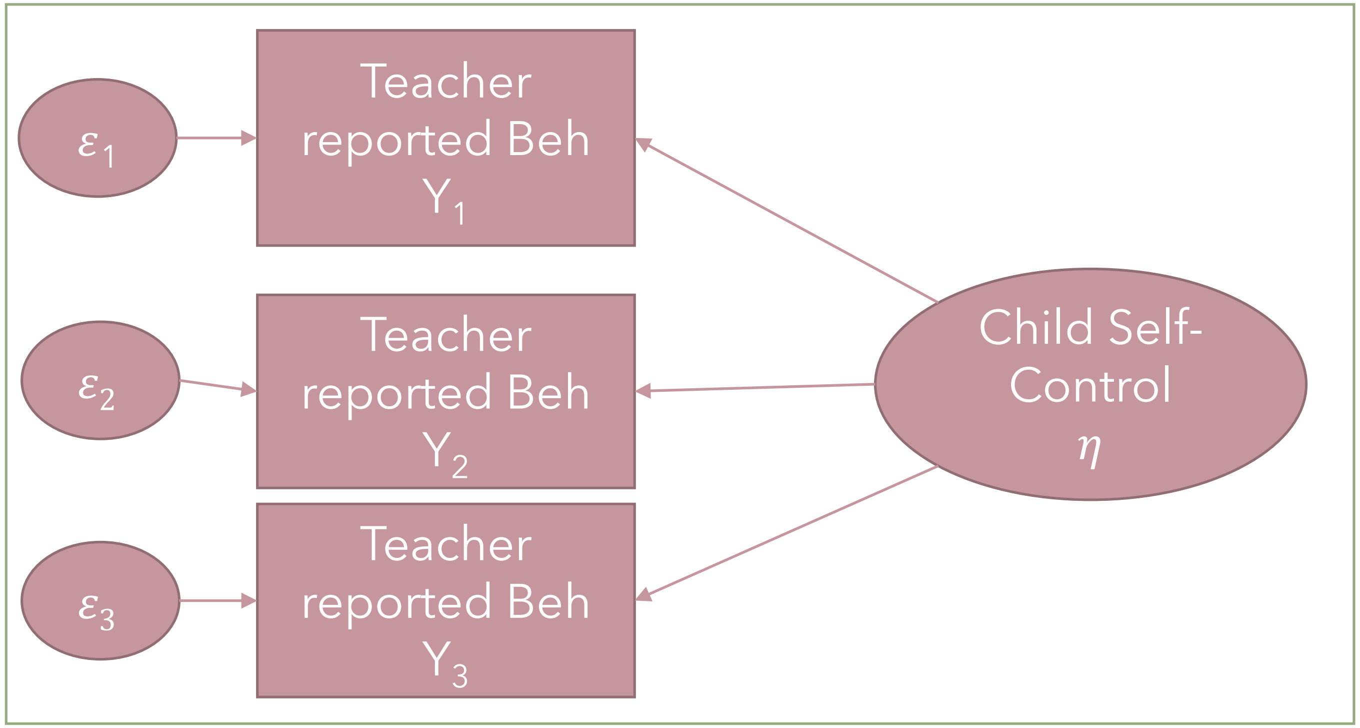
Moving beyond the measurement model

- Using an observed variable as a predictor of the latent categorical variable
- Using the latent categorical variable as a predictor of an observed variable

Structural and Measurement Models

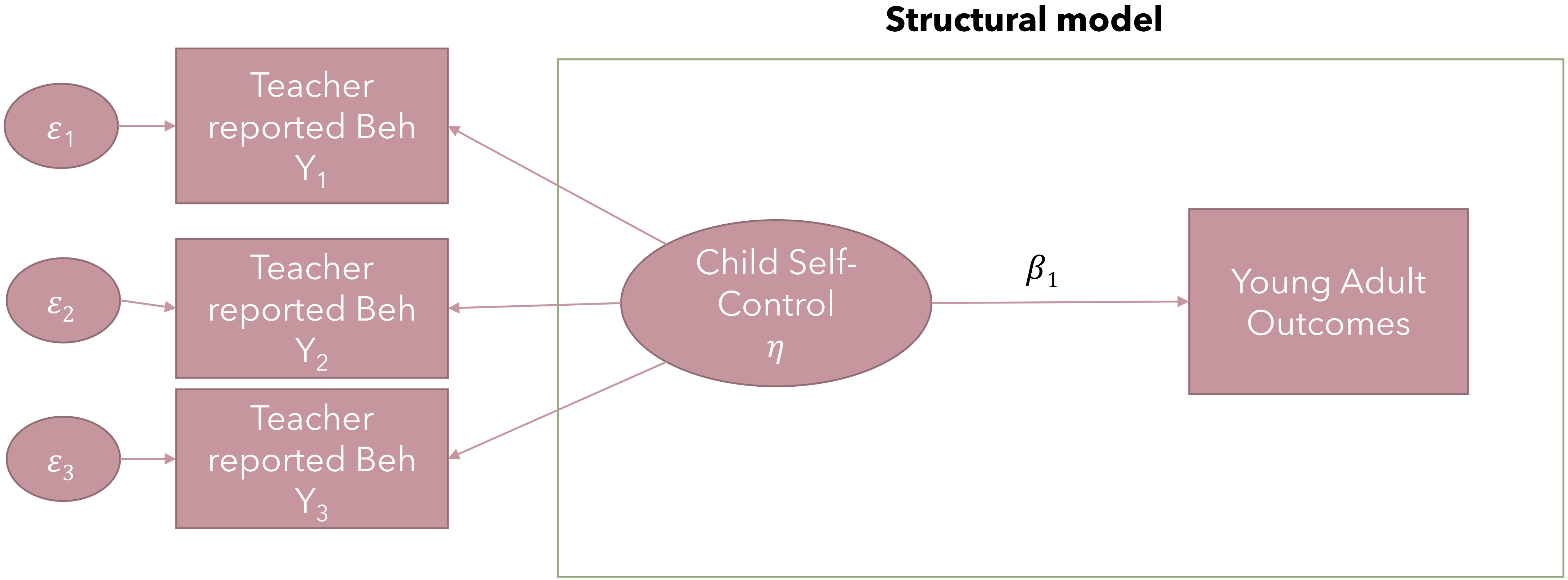
+ Does self-control in childhood predict outcomes in young adulthood?

Measurement model



Structural and Measurement Models

+ Does self-control in childhood predict outcomes in young adulthood?



Latent Class regression Methods

+ **Automatic methods:** utilize in-software code to assess relationships

+ **3 step methods:** allow you to have more control over how the relationship is estimated

  BCH weights or Logit methodologies

BCH method

- Described by Vermunt (2010) , simulations in Bakk & Vermunt (2014)
- Uses a weighted multiple group analysis, groups correspond to the latent class
  - Weights reflect the measurement error of the latent class variable
  - Class shifting doesn’t occur because the classes are ‘known’
- Performs well when the variance of the aux variable differs substantially across classes

Does self-control in childhood predict outcomes in young adulthood?

		Latent classes of self-control (SC)			
		High (48.1%)	Inattentive (35.4%)	Inattentive/hyperactive (16.6%)	
Outcomes	Full sample (100%)	[1]	[2]	[3]	Pairwise comparisons ($p < .05$)
On-time HS graduation*	56.3	67.3	51.1	31.7	1 > 2; 1 > 3
College participation*	44.7	53.9	38.4	28.4	1 > 2; 1 > 3
Incarceration	9.4	6.0	11.4	15.9	–
CJS involvement^	22.7	17.1	29.5	25.0	1 < 2; 1 < 3
Teen pregnancy^	47.7	44.4	53.4	44.4	1 < 2
Substance use disorder	13.0	11.7	12.5	18.7	–

Notable advances in LCA

+ Confirmatory LCA

Should be used when existing literature readily points to a class structure

Organizational Research Methods
Volume 21, Issue 4, October 2018, Pages 983-1001

https://doi.org/10.1177/1094428117747689

SAGE journals

Article

Confirmatory Latent Class Analysis: Illustrations of Empirically Driven and Theoretically Driven Model Constraints

Sarah J. Schmiege[1], Katherine E. Masyn[2], and Angela D. Bryan[3]

Notable advances in LCA

+ Multi-level latent class analysis

  Useful when trying to understand how latent classes at the individual level work at level 2.

  See Henry & Muthén (2010) for a nice tutorial (with code!)

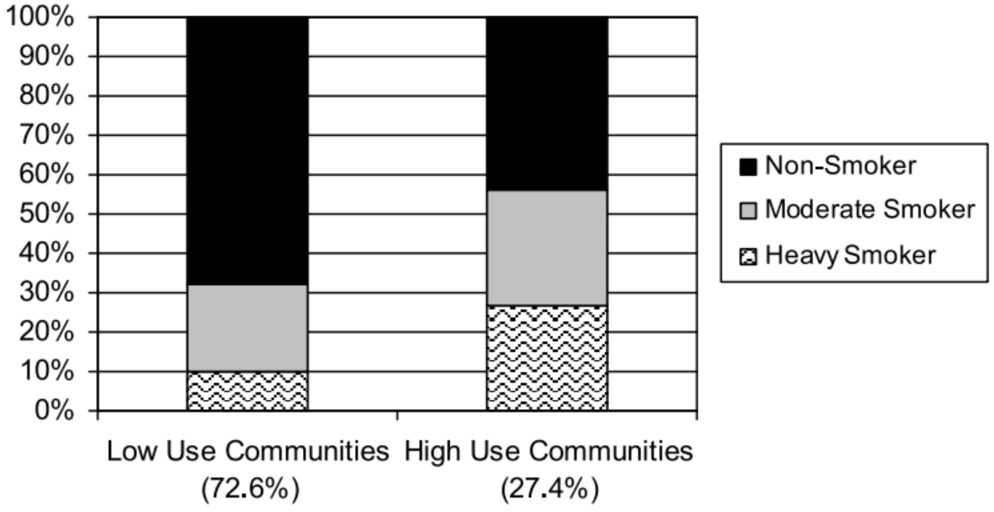


FIGURE 8 Non-parametric multilevel latent class solution, $C = 3$, $CB = 2$.

Notable advances in LCA

+ Easier methods for testing and handling instances of measurement non-invariance

DOI: 10.1111/cdev.13691

EMPIRICAL ARTICLE

CHILD DEVELOPMENT

Latent classes of aggression and peer victimization: Measurement invariance and differential item functioning across sex, race-ethnicity, cohort, and study site

Amie F. Bettencourt[1,2] | Rashelle J. Musci[2] | Katherine E. Masyn[3] | Albert D. Farrell[4]

Measurement invariance

- statistical property of measurement that indicates that the same construct is being measured across specified covariates.
- A simple example: two individuals (i, j) in the same latent class (k) but have different values on a covariate (x)
  - A latent class indicator U has measurement invariance for class k with respect to X IF those two individuals have the same expected response to U

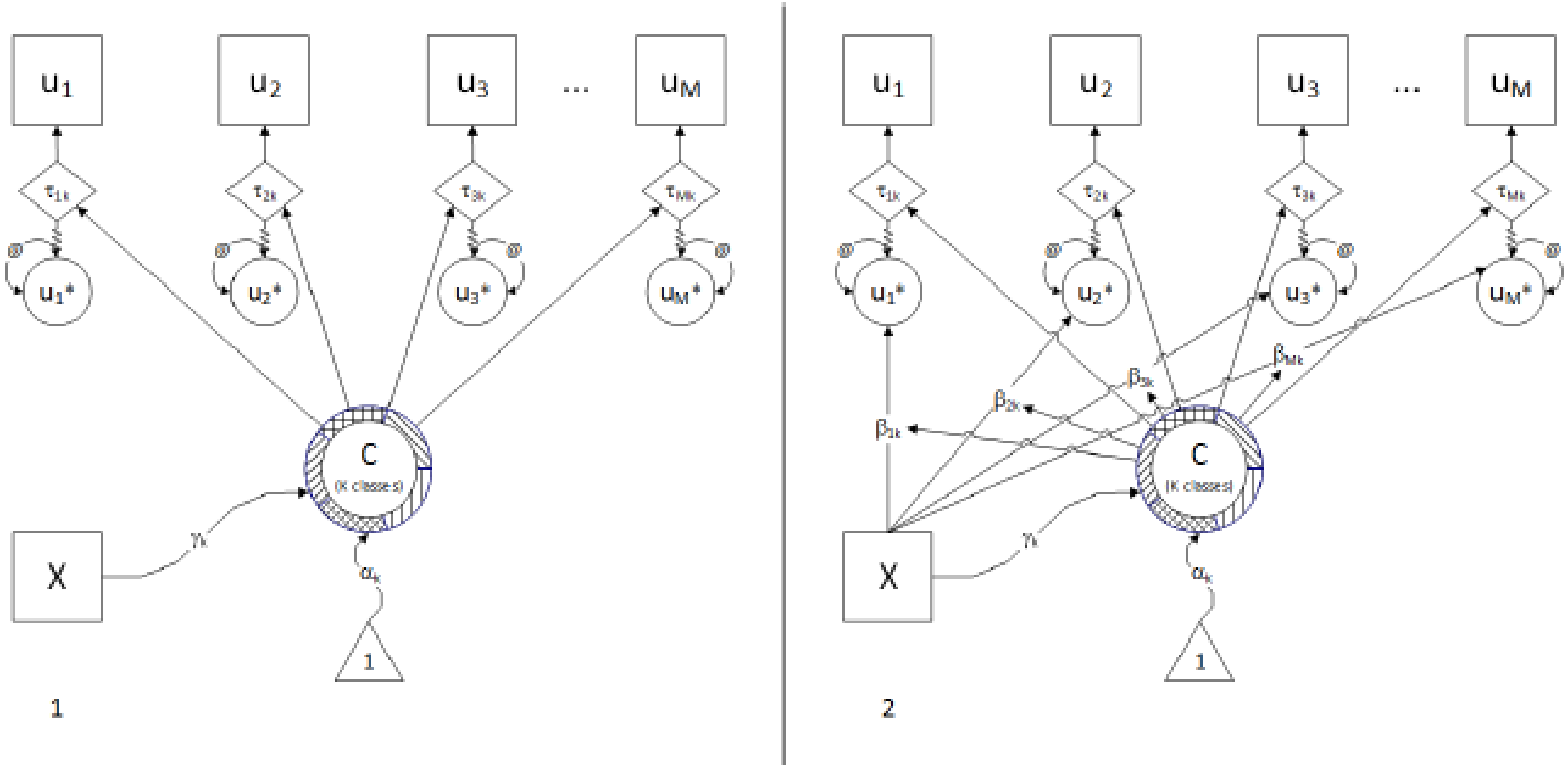


Figure 3. Path diagrams for (1) the no-DIF latent class MIMIC model M1.0 of Step 1 and (2) the all-DIF latent class MIMIC model M1.1 of Step 1.

Additional considerations

- Statistical power can be challenging to address with mixture modeling

  We have to rely on simulation studies or prior work to support our estimated sample sizes

- See Kim, 2012 and Dziak et al., 2014

Missing	*Separation*	*Classes*	*Indicators*	*Parameters*	*Required Sample Size*
Complete	High	2	4	15	200
			7	18	200
		6	4	31	300
			7	34	400
	Low	2	4	15	700
			6	17	500
			8	19	500
			10	21	500
		6	4	15	2,400
			5	16	1,500
			6	17	1,200
			7	18	1,100
			8	19	1,000
			9	20	1,000
			10	21	800
20% missing	High	2	4	15	200
			7	18	200
		6	4	31	400
			7	34	300
		2	4	15	800
			6	17	600
			8	19	600
			10	21	300
		6	4	15	3,000
			5	16	2,000
			6	17	1,600
			7	18	1,600
			8	19	1,200
			9	20	1,100
			10	21	1,100

Common Latent variable Software & Programs

+ Mplus
+ Lavaan or SEM in R (among other packages)
+ SEM and GSEM in Stata
+ Latent Gold
+ SAS

Thank you!

Feel free to reach out:

rmusci1@jhu.edu